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RESEARCH ON NEW TECHNIQUES FOR THE ANALYSIS OF MANUAL CONTROL SYSTEMS

PROGRESS REPORT NO. 7

George A. Bekey
Michael J. Merritt

June 16, 1968 - December 15, 1969

Prepared for the National Aeronautics and Space Administration under Grant Number NGR 05-018-022.

ELECTRONIC SCIENCES LABORATORY

USC Engineering

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I. INTRODUCTION

During the past six months the application of stochastic approximation techniques to the identification of parameters in human controller models was further developed and a report was completed for distribution. New results were also obtained in the identification of sampling intervals and other parameters in discrete models of human operator behavior. The results were based in part on a study of sampled data models of the describing function type and in part on discrete models of the hybrid block structure type. In the area of neuromuscular systems, a combination of analytical and computer techniques was applied to the development of a mathematical model of skeletal muscle function in isometric tasks.

In addition to the above research projects, a tutorial survey of manual control systems was written for publication. A description of the above projects is contained in the following pages.

II. THE IDENTIFICATION OF HUMAN OPERATOR MODELS BY STOCHASTIC APPROXIMATION

C. B. Neal, G. A. Bekey and M. J. Merritt

The main objective of this research is the application of stochastic approximation techniques to the identification of parameters in sampled models of dynamic systems, including those which involve hypothesized discrete models of human controllers. Since the last report, the first phase of this work has been completed and C. B. Neal's dissertation [1] has been completed and will be issued as a report in the near future. The theoretical aspects of this work will be submitted to the 1969 Joint Automatic Control Conference for presentation as an invited paper [2] and will be submitted for publication to the IEEE Transactions on Automatic Control. The aspects of this research most particularly concerned with the description of human operators will be presented at the 1969 MIT-NASA Conference on Manual Control [3].

The abstract of C. B. Neal's dissertation follows:

ABSTRACT

Various methods have been proposed to estimate the parameters of both open loop and closed loop sampled-data control systems. Generally speaking, these methods yielded approximate models of the system under study; the degree of approximation depending on the a priori knowledge of the system structure, state observation noise, system nonlinearities, and other factors. However, none of the methods has been applied to the problem of determining the sampling interval of either closed loop or open loop sampled-data control systems. This has been the task of the present study. Specifically,

this dissertation is concerned with estimation of parameters in systems that have internal sampling, but have continuous input and output. The continuous portion of the sampled-data system is given by the differential equation

$$\frac{dz}{dt} = f(z, p, u(t)); \; z(t=0) = \zeta$$

where z is an n dimensional vector of state, $f(\cdot)$ is the n dimensional vector of the dynamical system, p is a constant h dimensional vector of parameters, u(t) is an r dimensional vector of piecewise continuous control functions, and ζ is the initial condition vector. For our results, $f(\cdot)$ was required to be of class C^1 in z and p. The differential equation is preceded by some form of data hold. The model-matching technique was used for parameter estimation. Methods were developed for determining not only the sampling interval, but all the other parameters and initial conditions of the sampled-data system as well.

In this investigation, three methods were employed for the estimation of sampling intervals and other parameters of a sampled-data system. In all methods, the cost function was the integral of norm-squared error, where the error function was defined as the difference between the observed state vector of the system, and the state vector of the model.

The first method employed programmed search to vary the model parameters in order to minimize the cost function.

The second method employed iterative gradient search by means of discrete sensitivity difference equations for the various model parameters. The work of Bekey and Tomovic in connection with discrete sensitivity difference equations for the sampling interval was extended to all the other parameters of the system. Gradient search was then used for parameter estimates.

The third, and most important, method used was that of stochastic approximation. This permitted observation noise. The mean-square convergence of the model parameters to the true parameters of the system was proved under the following conditions: The systems and model agreed in form and order, the data holds were identical, the observation noise had zero mean, finite variance, and was uncorrelated with both the system state vector and model state vector, $f(\cdot)$ was of class C^1 in z and p, and the partial derivative of the cost function with respect to the sampling interval existed and was bounded.

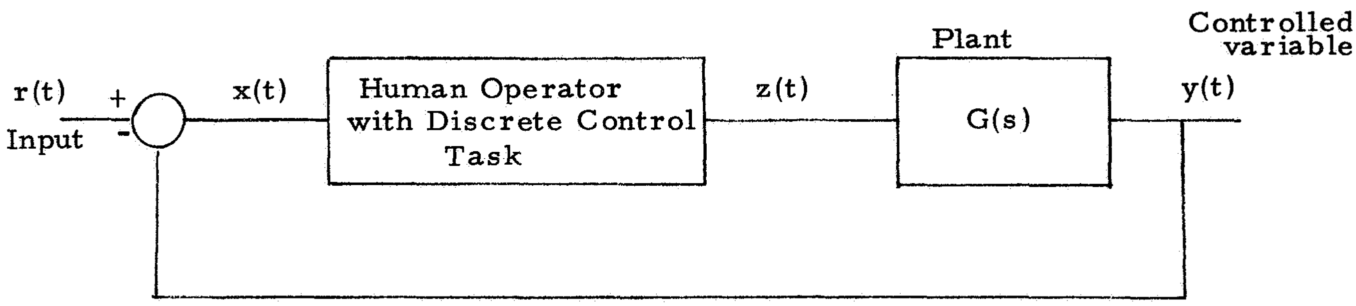
Stochastic approximation was then applied to the practically important problem of estimating the parameters of the human operator from records of scalar input and scalar output of the human operator operating in a closed loop configuration. Parameters were estimated successfully in both continuous and sampled-data models of human operators.

III. DISCRETE HUMAN OPERATOR MODELS

M. J. Merritt and G. Meier

The development of mathematical models which describe discrete human operator control actions has been discussed in references 4, 5 and 6. The models utilized two basic building blocks: the Multi-State Decision Element (MSDE) and the Proportional Decision Element (PDE). Identification procedures for both elements are given in reference 5. However, the procedures for the MSDE are not satisfactory.

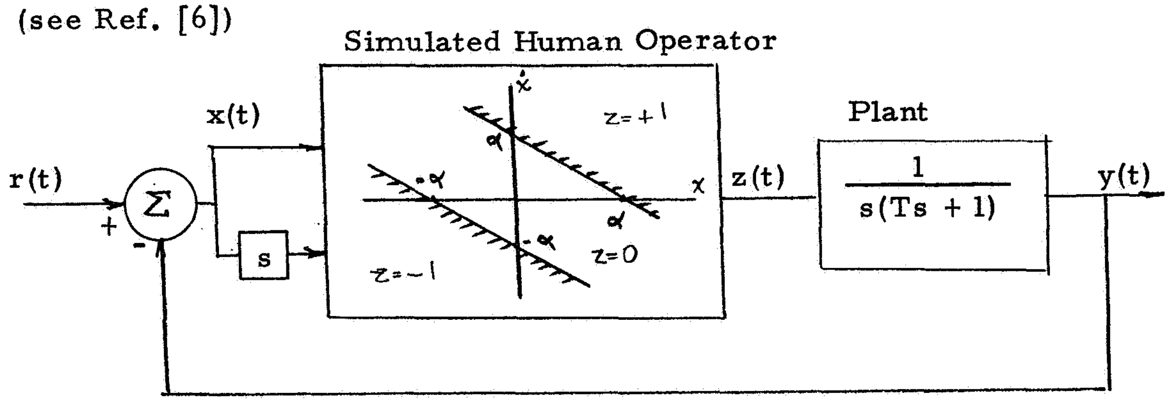
Consider the following manual control task in which the human operator



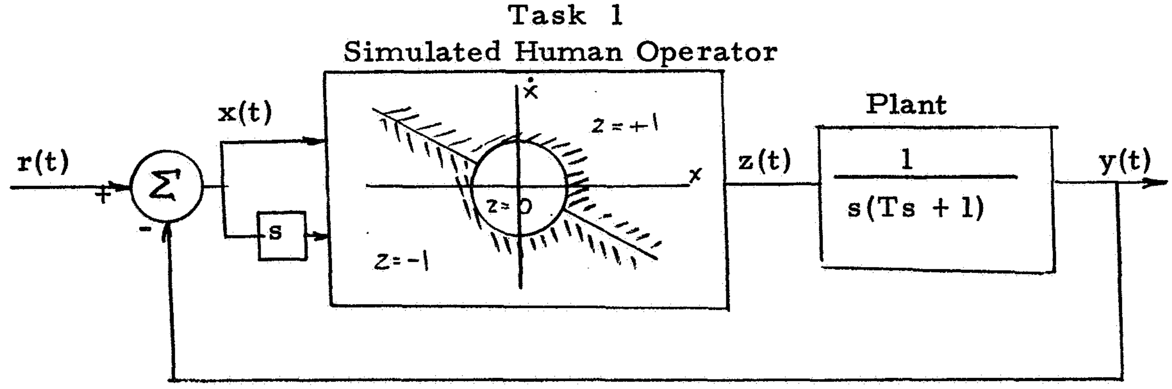
elects to produce the discrete control actions +1, 0 and -1. Although the only direct input to the human operator is $x(t)$, the human operator is capable of estimating $\dot{x}(t)$. Thus the decision policy will, in general, be a function of both $x(t)$ and $\dot{x}(t)$. Previously, the number of input state variables was increased, through the inclusion of algebraic functions of x and $\dot{x}$, until hyper planes could be used as decision surfaces. Interpretation of the hyper plane decision surfaces in the original input space, x and $\dot{x}$ was difficult.

Under development are digital computer programs which will locate decision surfaces and volumes in multi-dimensional decision spaces and approximate them using a set of parametric figures. The dimensionality of the problem will be that of the input state space and will not be artificially increased. Interpretation of the decision boundaries will present no difficulties.

Two manual control tasks have been simulated and input-output data obtained. This data will be used to test and improve the identification procedures. The two tasks are shown in the figures below ; (see Ref. [6])



Task 1



Task 2

IV. IDENTIFICATION OF SAMPLING INTERVALS IN SAMPLED DATA MODELS OF HUMAN OPERATORS

C. B. Neal and G. A. Bekey

In the past they synthesis of sampled data models of human controllers has been hampered by the lack of systematic procedures for estimating sampling frequency to be used. in the model. In Section II above, we have described the use of stochastic approximation to identify model sampling intervals. In addition, program search and gradient techniques have been successfully employed to determine unknown sampling frequencies in closed loop sampled data systems whose structure closely approximates sampled data models of human operators as previously published [7]. A paper, describing these results, has been accepted for publication in the IEEE Transactions on Man Machine Systems. The paper is included in full as an appendix to this report.

V. MATHEMATICAL MODELS OF SKELETAL MUSCLE

J. C. Coggshall, G. A. Bekey and G. P. Moore

The dissertation of J. C. Coggshall, describing his synthesis of mathematical models of human skeletal muscle in isometric tasks, was completed during the report period. The abstract of the dissertation [8] follows:

ABSTRACT

This dissertation presents the formulation and development of models describing the dynamic behavior of skeletal muscle. The specific muscles studied were those responsible for forearm extension in a normal human.

The models relate the surface myoelectric activity recorded from a muscle to the output force produced by that muscle in isometric tasks.

Previous attempts to relate the myoelectric activity to muscle performance have only been carried out in the static case.

The models proposed in this study are linear differential equations whose input is the rectified myoelectric signal. The differential equation was simulated on an analog computer.

The actual parameters of the model were identified by using an on line analog computer mechanization which minimized a quadratic function of the difference between model output and actual muscle output.

The statistical properties of the surface myoelectric signal are treated analytically. It is shown how its statistical properties in general and the time-varying root-mean-square value in particular can be related to the underlying physiological events.

VI. OTHER PUBLICATIONS

A tutorial chapter entitled "The Human Operator and Control Systems" has been written as a contribution for a book to be entitled Psychological Factors in Systems, edited by Dr. K. B. DeGreene, to be published by McGraw-Hill Book Company in 1969. The chapter is being reissued as a USC report and will be distributed during the next report period.

A new paper entitled "Decision Processes in the Adaptive Behavior of Human Controllers" is being prepared by A. V. Phatak and G. A. Bekey. This paper is based on the dissertation research of A. V. Phatak, which was described in the previous progress report, and published as a USC report [9]. The paper will be submitted to the 1969 Manual Control Conference and to the IEEE Transactions on System Science and Cybernetics for publication.

VII. GRAPHIC DISPLAY SYSTEM

M. J. Merritt and G. A. Bekey

Under a grant from the National Science Foundation a graphic display system will be obtained during the next report period, and interfaced to the USC hybrid computer system (IBM 360/44-Beckman 2132). The availability of an interactive graphic terminal will make possible the investigation of a variety of problems in manual control and man machine systems in which a computer generated display is essential.

REFERENCES

1. Neal, C. B. "Estimation of the Parameters of Sampled-Data Systems by Stochastic Approximation", Ph.D. Dissertation, Univ. of So. California January 1969 (Also issued as USC Electronic Sciences Laboratory Report, USCEE 333).

2. Neal, C. B. and Bekey, G. A. "Estimation of Parameters of Sampled-Data Systems by Stochastic Approximation" to be presented at Joint Automatic Control Conference, Boulder, Colorado, August 1969.

3. Neal, C. B. and Bekey, G. A., "Identification of Human Operator Models by Stochastic Approximation", to be presented at MIT-NASA Conference on Manual Control, March 1969.

4. Merritt, M. J. and Bekey, G. A. "An Asynchronous Pulse-Width, Pulse-Amplitude Model of the Human Operator", Proc. 3rd NASA-University Conference on Manual Control, NASA SP-144, pp. 225-240, 1967.

5. Merritt, M. J. "Synthesis and Identification of Mathematical Models for the Discrete Control Behavior of Human Operators", Ph.D. Dissertation, University of Southern California, 1967 (Also issued as USC Electronic Science Laboratory Report, USCEE 202, 1967).

6. Merritt, M. J. "The Application of Discrete Modeling Elements to the Synthesis and Identification of a Deterministic Model for the Visual Scanning Behavior of Human Operators", presented at the NASA-University of Michigan Conference on Manual Control, 1968.

7. Bekey, G. A. "The Human Operator as a Sampled Data System", IRE Trans. on Human Factors in Electronics, v. HFE-3, pp. 43-51, Sept. 1962.

8. Coggshall, J. C. "Mathematical Models of Muscle", Ph.D. Dissertation, University of Southern California, 1968 (Also issued as USC Electronic Sciences Laboratory Report USCEE 303, August 1968).

9. Phatak, A. V. "On the Adaptive Behavior of the Human Operator in Response to a Sudden Change in the Control Situation", Ph.D. Dissertation, University of Southern California (Also issued as USC Electronic Sciences Laboratory Report USCEE 277, May 1968).

APPENDIX

Identification of Sampling Intervals in Sampled Data Models of Human Operators

G. A. Bekey*

C. B. Neal**

ABSTRACT

The synthesis of sampled-data models of human controllers has been hampered by the lack of systematic procedures for estimating the sampling frequency to be used in the model. This paper presents two methods (programmed search and gradient search) for the determination of an unknown sampling frequency in closed-loop sampled-data systems. Both methods are based on a-priori knowledge of the structure of the system to be identified and require only measurements of the continuous input and output of the system.

Several theorems concerning the identification problem are presented. The application of both the gradient search and programmed search techniques is illustrated by several examples.

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I. INTRODUCTION

Mathematical models of human operators involving some form of sampling have been proposed for several years[1-3]. However, in all the techniques proposed to date, a systematic technique for estimating the sampling frequency employed by the human operator has been lacking. Rather, indirect and more or less heuristic techniques have been used. Furthermore, since recent studies[4, 5] have indicated that if human operators do sample, they probably do not employ a constant sampling frequency, it is necessary to develop a systematic estimation procedure which can be employed successfully even when the sampling interval undergoes some random variation.

A number of techniques for parameter identification in both continuous and discrete systems are well known, e. g. gradient methods, random search, relaxation, and quasi-linearization. However, these techniques have not been applied to systems where the sampling frequency is one of the parameters to be identified. The problem is of particular interest in closed-loop systems with error sampling, where only the continuous input and continuous output are observable. This situation characterizes closed-loop compensatory tracking tasks involving human operators, in which both the visual input and control variables were continuous.

The purpose of this paper is to demonstrate the applicability of programmed search and gradient methods to the identification of unknown sampling frequencies (and other parameters) in discrete dynamic systems which resemble sampled data models of human operators. The technique is restricted to the constant sampling frequency case. A later paper will be concerned with the application of stochastic approximation to parameter estimation using actual human tracking data, where both parameter noise and observation noise can be assumed to exist.

II. STATEMENT OF THE PROBLEM

Consider the simple human operator model shown in Figure 1. This model was used to represent human operator compensatory tracking behavior in simple tasks were the controlled element dynamics were negligible[3]. It is evident that there are four unknown parameters in this model, namely the sampling frequency T, the gain K, the model time delay D, and the time constant T_N. If we assume that only the reference input and control variable are observable, the basic identification problem can be illustrated by Figure 2. Here both system and model are denoted by vector differential equations and the quantities $y_1(t)$ and $y_{m1}(t)$ indicate the (scalar) outputs. The system has an unknown sampling frequency f_x (or sampling interval $T_x = 1/f_x$) while the model has an adjustable sampling interval T_a. The following assumptions are made:

a) The structure of the system is known a-priori; therefore, the data holds and dynamics of the system and model agree exactly. Thus the only unknown factor is the sampling interval T_x. Later, the requirement that system and model agree will be relaxed.

b) The system and model are noise-free.

c) The differential equations of the system and model have unique solutions.

This means that if

$$\dot{y} = f(t, y(t), u(t)) \qquad (1)$$

is the form of the vector differential equation for both the system and model then both $f_i(\cdot)$ and $\frac{\partial f_i}{\partial y_j}(\cdot)$ must be continuous and bounded for all i and j.

(In Eq. 1, y and f are r-dimensional vectors, and u is an $m \leq r$ vector.)

The problem can now be stated as follows: Given the configuration of Figure 2 and the above set of assumptions, find the sampling interval T_a which minimizes the criterion function

$$J(T;\ T_a) = \int_0^T [y_1(t) - y_{m1}(t,\ T_a)]^2 dt\ . \qquad (2)$$

III. ANALYTICAL FOUNDATION

Assuming that the minimization indicated in Eq. 2 can be accomplished, it is necessary to prove that the resulting value of T_a will indeed equal the unknown system sampling interval T_x. Under the conditions of Section II, the following theorems can be shown to hold[6]:

Theorem I: If the system and model are linear, then J is strictly convex over T_a. (The implication of this theorem is that convergence to a unique value of T_x may be expected when a convergent computer algorithm is used for the identification.)

Theorem II: The criterion function J cannot be zero on a T_a interval; J is zero for one value of T_a only.

Theorem III: A necessary and sufficient condition for the identification of a sampling interval T_x is that

$$\min_{T_a} \ J(T;T_a) = 0 \qquad (3)$$

and for this case $T_x = T_a$.

Hence, the minimization over T_a of the criterion function $J(T;T_a)$ does indeed lead to the desired solution.

IV. IDENTIFICATION OF T_x BY AN ITERATIVE DISCRETE GRADIENT METHOD

This method is based on the computation of a discrete sensitivity function u_T which provides a measure of the sensitivity of system response to variations in sampling interval T_a[7].

We assume that the system being identified can be described by the equation

$$\dot{y} = f(y(t),\ e_1(t),\ a) \tag{4}$$

where a is a vector of system parameters,

$$a = (a_1,\ a_2,\ \ldots\ a_n,\ T_x) \tag{5}$$

A model constructed in accordance with the assumptions of Sec. II is described by

$$\dot{y}_m = f(y_m(t),\ e_2(t),\ p) \tag{6}$$

with parameter vector

$$p = (p_1,\ p_2,\ \ldots\ p_n,\ T_a) \tag{7}$$

The criterion function of eq. (2) is evaluated over some interval $T >> T_a$. Also, the gradient vector is given by

$$\nabla_p J(T;p) = -2 \int_0^T [y_1(t) - y_{m1}(t,\ T_a)]\ \nabla_p y_{m1}(t;\ T_a)dt \tag{8}$$

where the gradient vector $\nabla_p\ y_{m1}$ is defined as

$$\nabla_p y_{m1} = \left(\frac{\partial y_{m1}}{\partial p_1}\quad \frac{\partial y_{m1}}{\partial p_2}\quad \cdots\quad \frac{\partial y_{m1}}{\partial T_a}\right)'$$

Each of these components of the gradient vector is a sensitivity function[8] with respect to the appropriate parameter. Then the iterative gradient adjustment follows according to

$$p^{(i+1)} = p^{(i)} - K^{(i)}\nabla_p J(T;\ p^{(i)}) \tag{9}$$

Now, for sampled-data systems, the sensitivity functions are most conveniently expressed by using a difference equation representation of the solution of the differential equation[7]. Corresponding to the differential equation of the model of eq. (6) there is a difference equation for the solution at sampling instants:

$$y_m[(n+1)T_a] = F_m[y_m(nT_a),\ e(nT_a),\ p] \qquad (10)$$

where n denotes the number of sampling intervals. ~~$n = 0, 1, \ldots . T/T_a$~~.

The sampling interval <u>global</u> <u>sensitivity</u> <u>function</u> is defined[7] by:

$$u_{T_a}(nT_a) = \left.\frac{\partial y_{m1}(t)}{\partial T_a}\right|_{t = nT_a} = \lim_{\Delta T_a \to 0}\left(\frac{y_{m1}[n(T_a + \Delta T_a) - y_{m1}(nT_a)]}{\Delta T_a}\right) \qquad (11)$$

where $n\,\Delta T_a << T_a$ for all n. This function is obtained by solution of appropriate sensitivity difference equations, as indicated in the following example.

<u>Example:</u> The identification scheme of Figure 2 is used with the system defined by $G_s(s) = \frac{K_1}{s}$ and the model defined by $G_m(s) = \frac{K_3}{s}$. Zero-order data holds are used in both loops. The initial conditions for both system and model are zero. The output of the model loop at the sampling instants is

$$y_m[(n+1)\,T_a] = y_m(nT_a) + T_aK_3[x(nT_a) - y(nT_a)] \qquad (12)^*$$

The sampling interval global sensitivity difference equation, using eq. (11) and eq. (12) is

$$u_T[(n+1)T_a] = [1-T_aK_3]u_T(nT_a) + T_aK_3\,\frac{1}{T_a}\left.(t\,\dot{x}(t))\right|_{t=nT_a} + T_aK_3\,\frac{\left(x(nT_a)-y(nT_a)\right)}{T_a} \qquad (13)$$

Similarly, the sensitivity function for the gain parameter is obtained from the solution of the difference equation

$$u_K[(n+1)T_a] = (1 - T_aK_3)\,u_K(nT_a) + T_aK_3[(x(nT_a) - y(nT_a))/K_3] \qquad (14)$$

where $u_K = \partial y_m / \partial K$. The solutions of eq. (13) and (14) are then substituted in eq. (8) to obtaine the gradient of the criterion function J(T;p). The corrected parameter vector is then obtained from eq. (9). The result of the gradient search for T_x alone is shown in Figure 3. The convergence to the correct value ($T_a = T_x = 0.25$ seconds) is evident. The result of search for both

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*The output of the example system is indicated simply as y_m (rather than y_{m1}) since the system is of first order.

K_1 and T_x is shown in Figure 4. A computer diagram for the two parameter case is shown in Figure 5.

V. PROGRAMMED SEARCH FOR T_x

An alternative to gradient methods is the use of programmed search[9] for obtaining the best estimate of T_x. Again, the modeling scheme of Figure 2 applies. Linear systems were chosen because their solutions from given initial conditions are unique. Programmed search was applied successfully to the system-model combinations of Table 1. Data holds were both zero order. The experimental results (Figure 6 and 7) indicate that when the model form is correctly chosen the presence of sampling can be detected quite readily by the minimum in the criterion function (J) curve. In the case where the model form is imperfectly known (in violation of Assumption 1 in Section II above), experimental results indicate the J curve may have no discernible minimum, as shown in Figure 8 (for the model of Experiment 3 in Table 1). The lack of a minimum can be taken as an indication that other models should be tried.

VI. CONCLUSION

Both gradient and programmed search have been applied successfully to the identification of unknown sampling intervals in closed-loop linear discrete-time systems, which resemble sampled-data models of human-operators in certain simple tasks. For those cases where the system form is known exactly and the sampling frequency is the only unknown, the identification rests on a solid analytical foundation. However, additional work is needed in the area of model-system mismatch and in the effects of disturbances before the technique can be applied to actual human tracking data.

REFERENCES

1. K. J. W. Craik, "Theory of the human operator in control systems", Brit. J. Psych., vol. 38, pp. 56-61, 1947; vol. 38, pp. 142-148, 1948.

2. L. P. Lemay and J. H. Westcott, "The simulation of human operator tracking using an intermittent model", Internat'l Congress on Human Factors in Electronics (Long Beach, Calif., May 1962).

3. G. A. Bekey, "The human operator as a sampled-data system", IRE Trans. Human Factors in Electronics, vol HFE-3, pp. 43-51, September 1962).

4. D. McRuer, E. Krendel, D. Graham, and W. Reisener, "Human pilot dynamics in compensatory systems", U.S. Air Force Report AFFDL-TR-65-15, July 1965.

5. G. A. Bekey, J. M. Biddle, and A. J. Jacobson, "The effect of a random-sampling interval on a sampled-data model of the human operator", Proc. 3rd Annual Conference on Manual Control, NASA Publications SP-144, 1967, pp. 247-258.

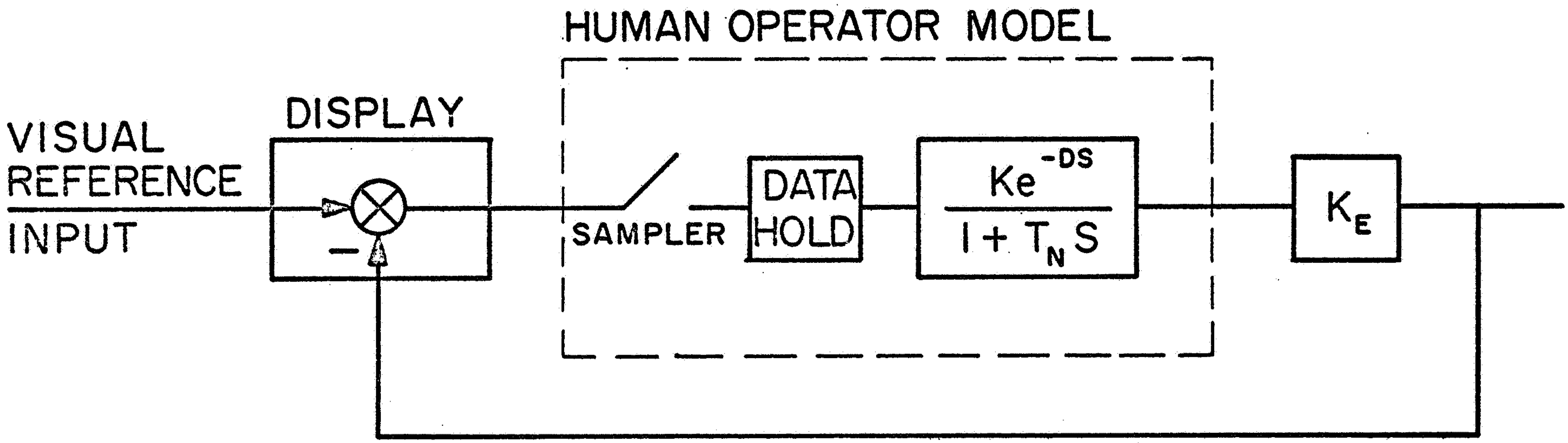
6. C. B. Neal, "On the estimation of the parameters of sampled-data systems", Ph.D. Dissertation, Electrical Engineering Department, University of Southern California, December 1968.

7. G. A. Bekey and R. Tomovic, "Sensitivity of discrete systems to variation of sampling interval", IEEE Trans. on Automatic Control, vol. AC-11, pp. 284-287, April 1966.

8. R. Tomovic, Sensitivity Analysis of Dynamic Systems, New York: McGraw-Hill, 1963.

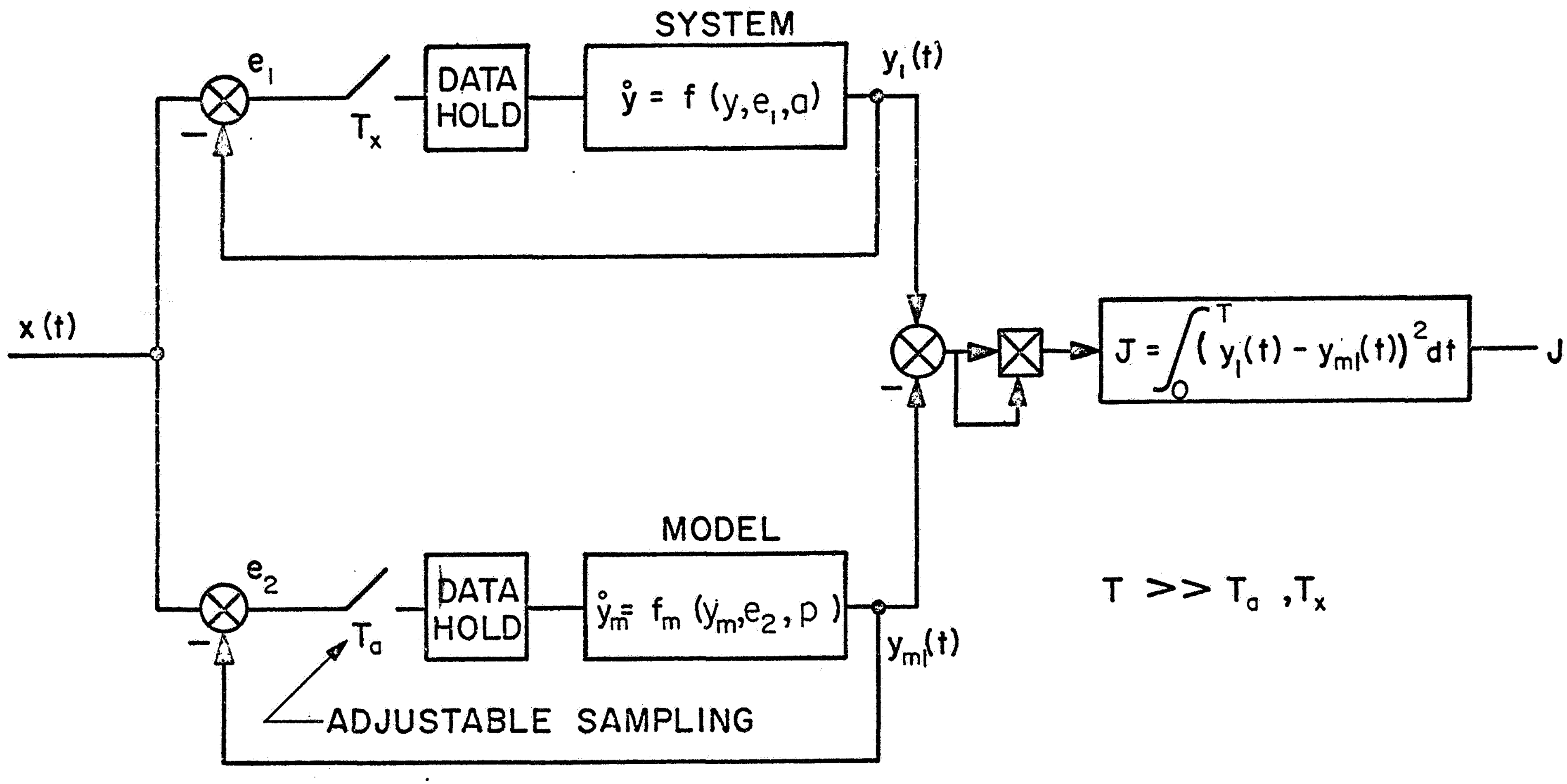
9. D. J. Wilde and C. S. Beightler, Foundations of Optimization, Englewood Cliffs, N. J.: Prentice-Hall, 1967.

LIST OF FIGURE CAPTIONS



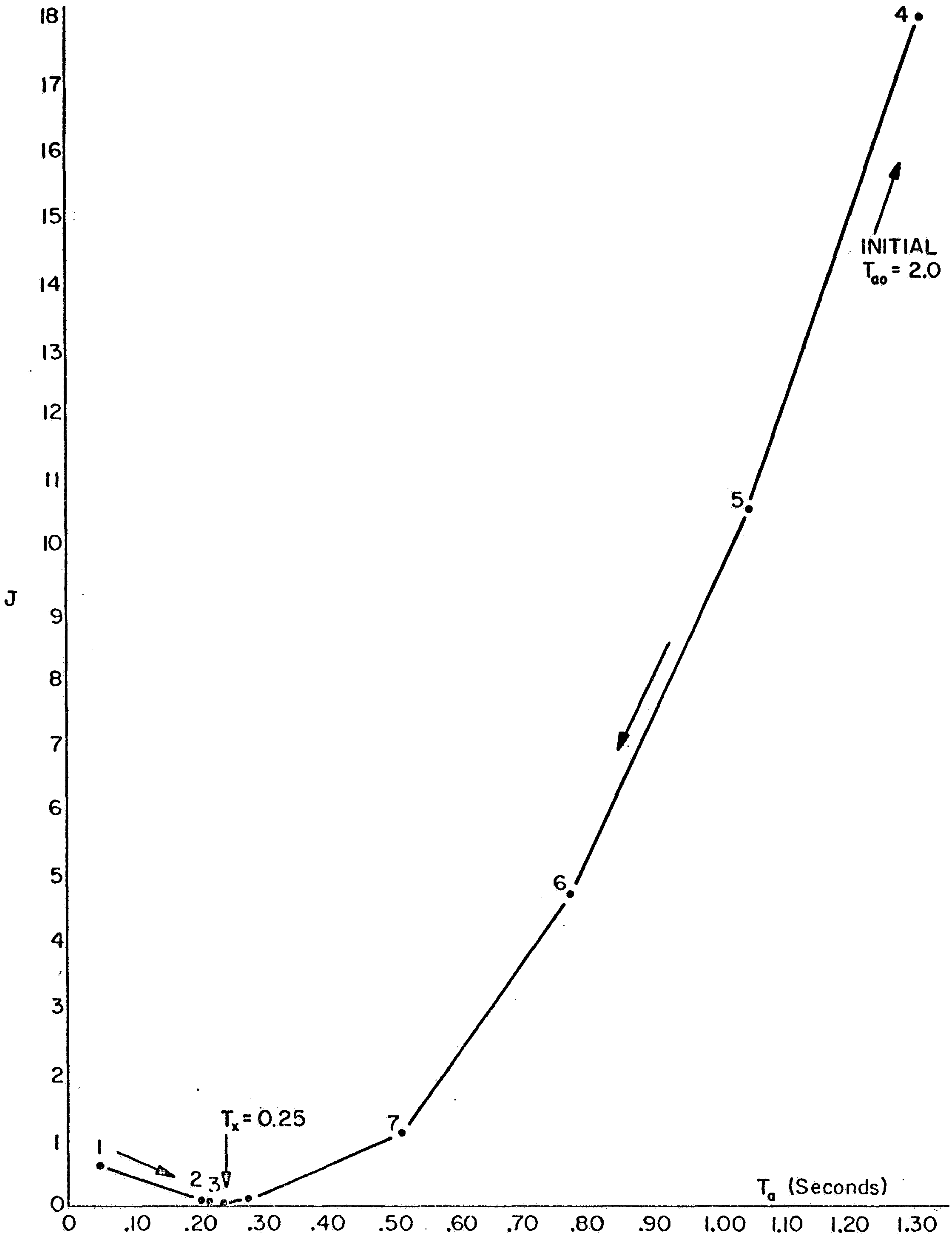
SAMPLED – DATA MODEL OF HUMAN OPERATOR IN COMPENSATORY TRACKING

FIGURE 1



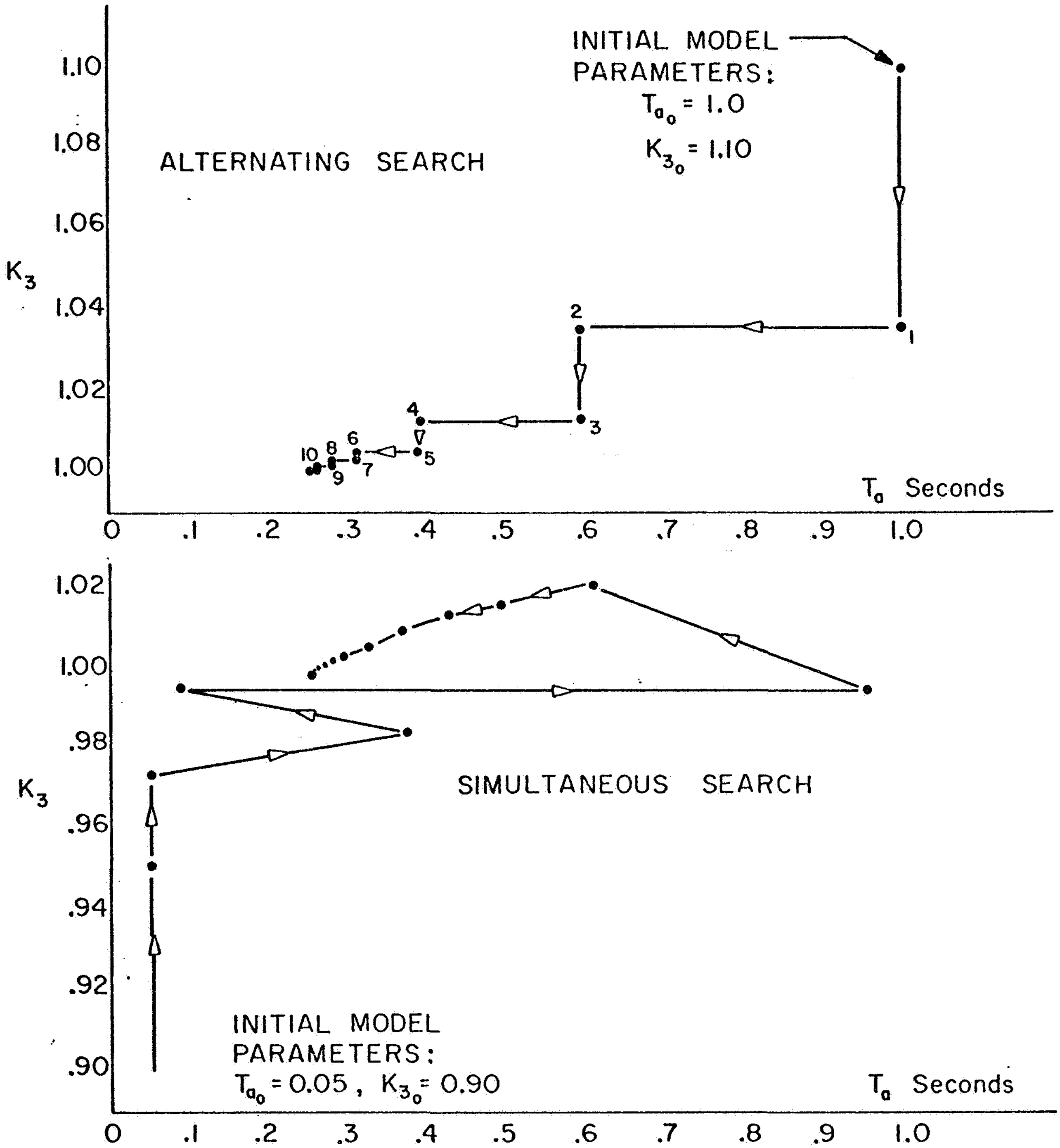
MODEL-REFERENCE CONFIGURATION

FIGURE 2



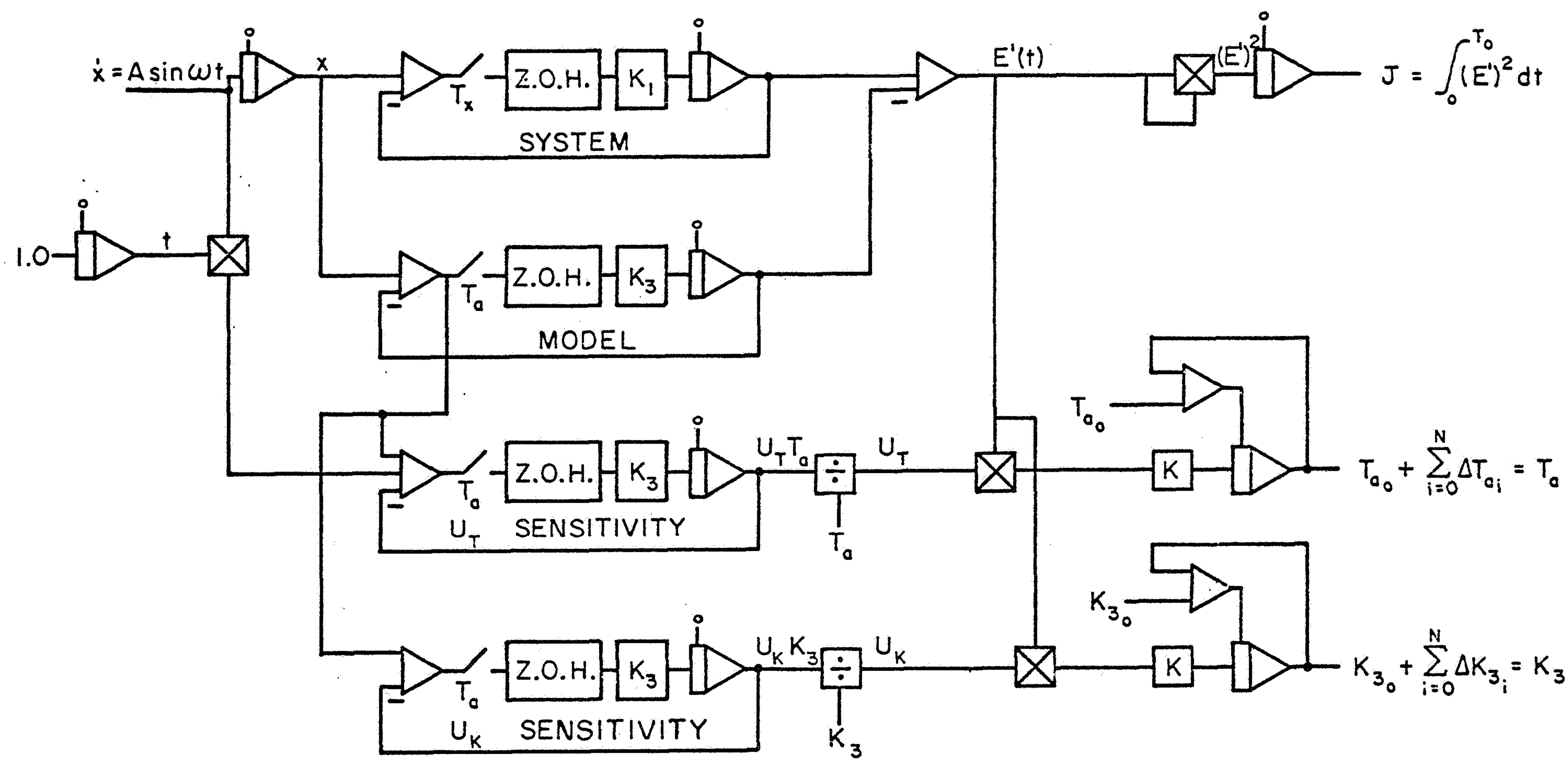
GRADIENT SEARCH FOR ESTIMATE OF T_x

FIGURE 3



GRADIENT SEARCH FOR ESTIMATE OF BOTH SAMPLING INTERVAL (T_x) AND GAIN (K_1) IN FIRST ORDER SYSTEM BY MEANS OF A FIRST-ORDER MODEL.

FIGURE 4

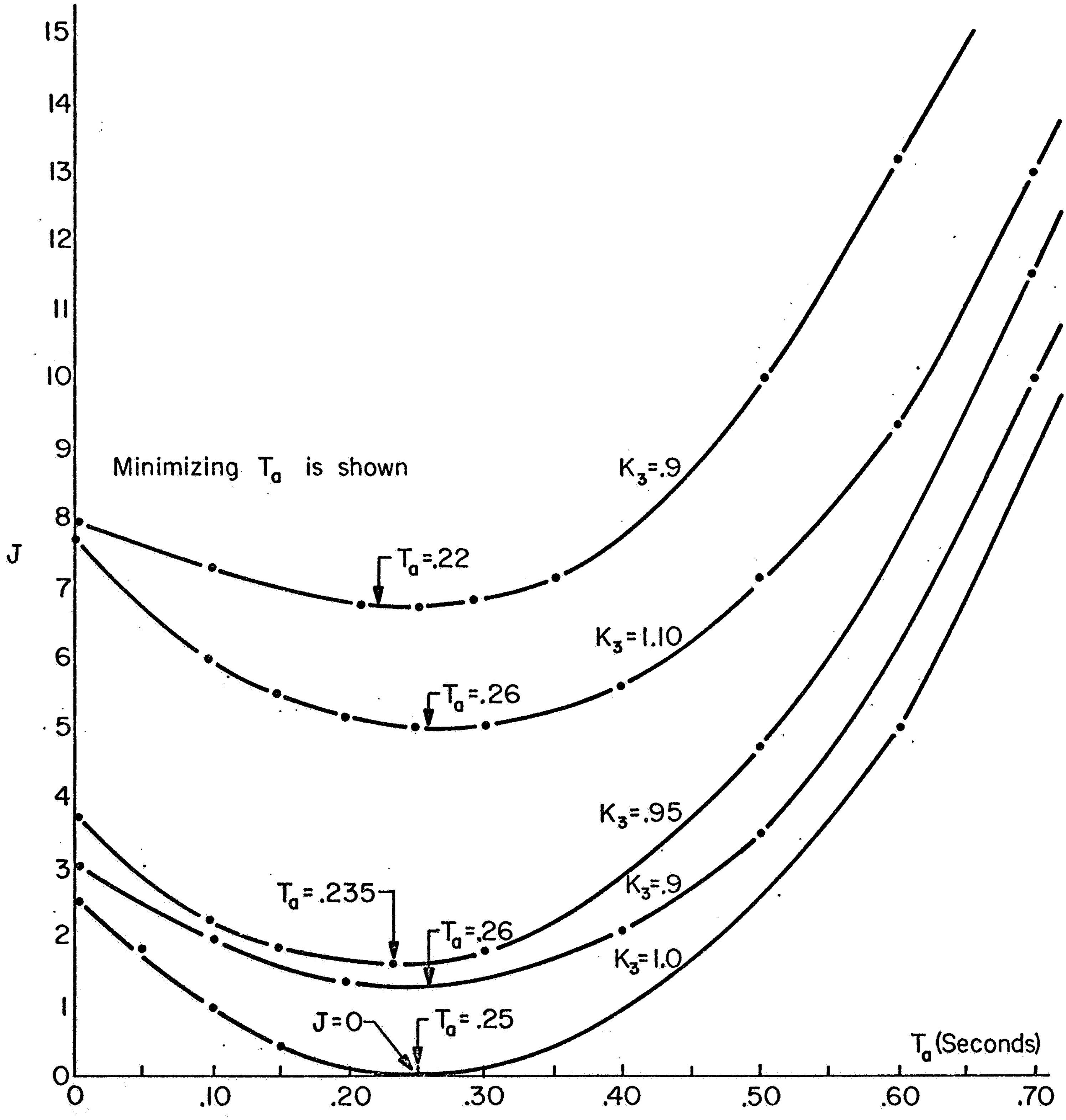


Notes

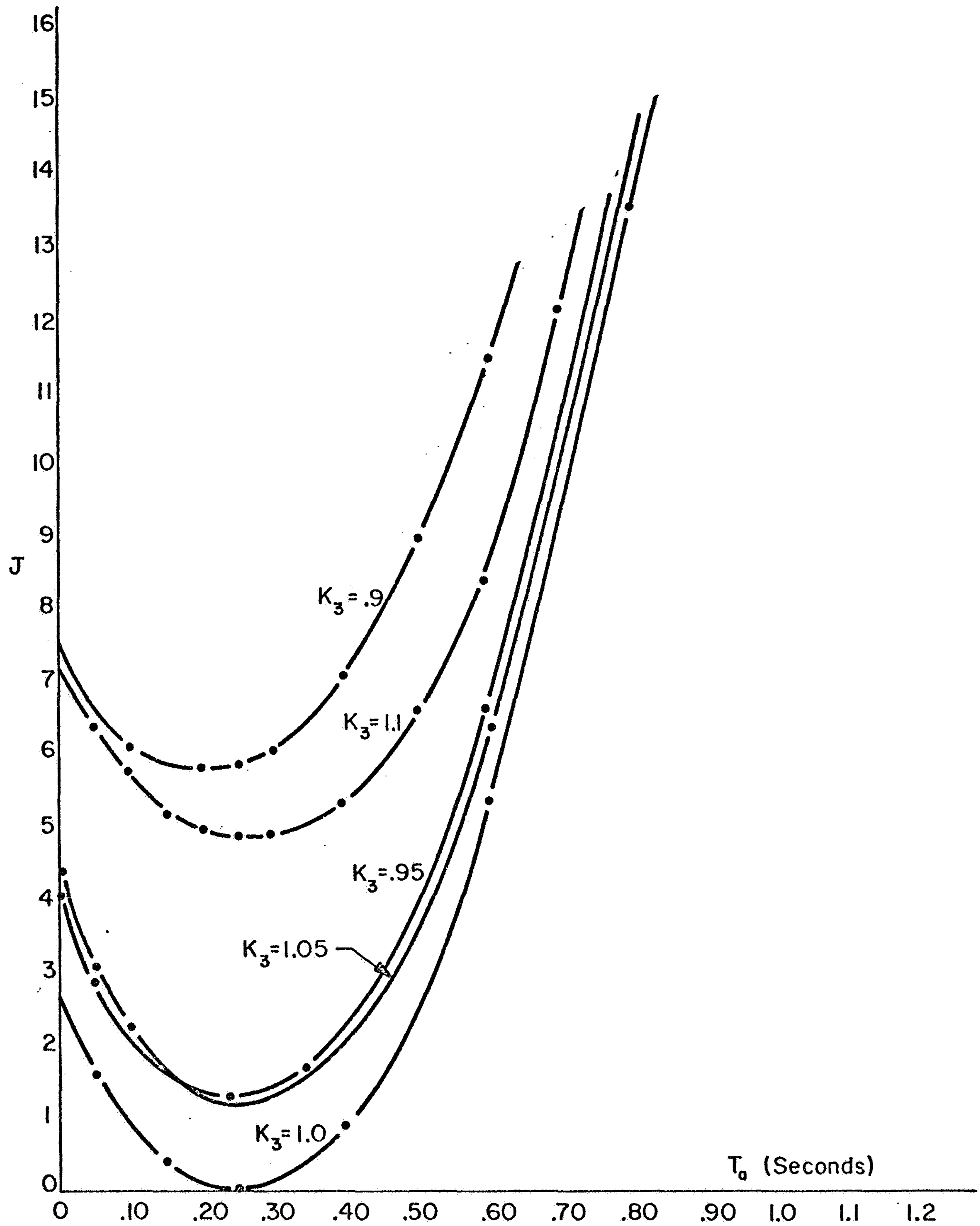
1. All integrations cycles are repetitive over $[0, T_0]$ - the iteration time.
2. After each iteration T_a and K_3 are adjusted to new values. Procedure continues until J is minimized.
3. Steep descent is used, hence K is a constant.

STEEP DESCENT IDENTIFICATION OF T_x AND K_1.

FIGURE 5

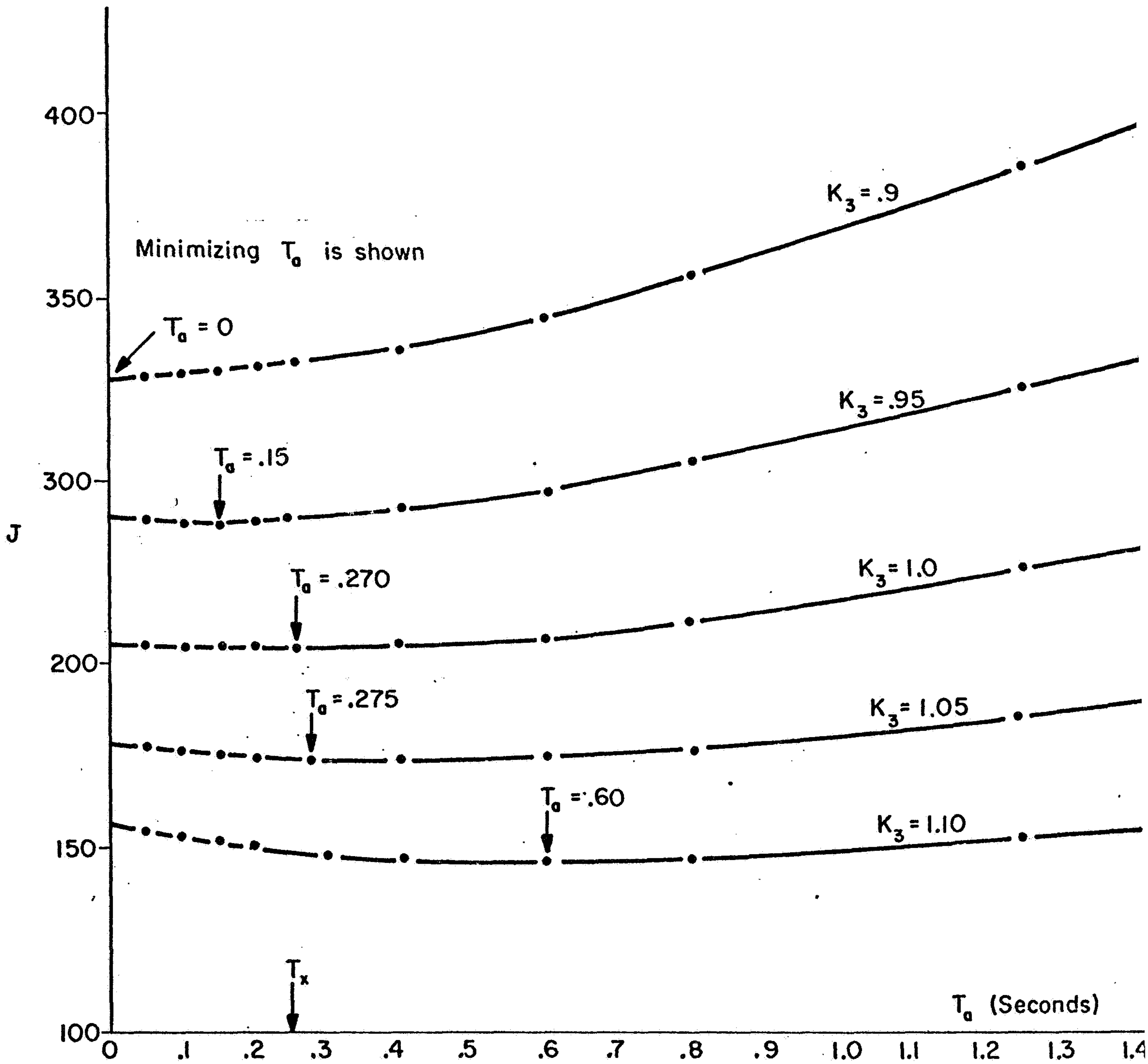


PROGRAMMED SEARCH FOR T_x — FIRST ORDER SYSTEM - MODEL MATCH
FIGURE. 6



PROGRAMMED SEARCH FOR T_x. BOTH SYSTEM AND MODEL HAVE TRANSPORT LAG

FIGURE 7



PROGRAMMED SEARCH FOR T_x. MISMATCH OF SECOND ORDER SYSTE[M] BY FIRST ORDER MODEL.

FIGURE 8.

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